CLASSIFICATION OF COMPOSITE DEFECTS USING THE SIGNATURE CLASSIFICATION DEVELOPMENT SYSTEM

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Abstract: The Johns Hopkins University Applied Physics Laboratory and the Carderock Division of the Naval Surface Warfare Center are developing a Signature Classification Development System (SCDS) to transfer classification technology to nondestructive evaluation (NDE) field equipment. SCDS is a personal-computer-based software tool-kit for developing classification algorithms. It includes support for digital signal processing, gating of the signatures, generation of feature vectors, and classification of vectors using artificial neural networks. SCDS successfully classifies ultrasonic signatures from defects in thick section, graphite/epoxy composite test panels. Seven test panels were fabricated with programmed defects embedded one-eighth or halfway into the panel. Six of the panels contain defects representing delaminations, porosity, and contaminations, and one panel serves as a reference standard. Ultrasonic signatures were recorded from the test panels using an ultrasonic C-scan system. SCDS was used to process the signatures and generate feature vectors for input to the artificial neural networks. The classifier achieved a 94% accuracy for one defect, and perfect accuracy for two other defects.

Keywords: Composites, defect 'assification, artificial neural networks, ultrasonics

INTRODUCTION: In 1966, manual ultrasonics was introduced into the U.S. Navy as an NDE inspection technique for welded structures [1]. Recent studies show that computer-assisted ultrasonics offers several benefits over conventional manual ultrasonics, including: an increased inspection speed [2], a more repeatable and reproducible inspection, less operator dependency, better evidence of weld coverage, the potential for improved consistency of length measurement, and an automatic, hard-copy of the inspection [3]. As a result, considerable effort is now being directed towards developing automated ultrasonic systems that size [4,5] and classify defects, and apply acceptance criteria [6].

Prior to the introduction of artificial neural networks (ANNs), classification algorithms were mainly limited to rule-based and statistical techniques [7]. Current research [8,9] demonstrates that ANNs can out-perform traditional techniques at classifying ultrasonic defect-signatures. Correct classification rates greater than 95% have been achieved using simulated weld-defects in laboratory studies [10,11], and about 90% for real weld-defects [2].

The U.S. Navy recognizes the recent advancements in computer-assisted ultrasonics, and the potential to produce reliable classification algorithms based on ANNs. To transfer this emerging technology to NDE field equipment, the U.S. Navy is developing the Signature Classification Development System. This system is a fully interactive, personal-computer-based package providing software tools necessary to build ANN classifiers for 2-dimensional NDE signatures. Automatic conversion of the developed classification algorithm into source code will permit integration of the classifier into computer-based NDE field equipment, increasing both the reliability and repeatability of inspection results.

Development of SCDS is an on-going effort, and this paper briefly presents the capabilities of the current version of SCDS, Version 1.02, where the targeted system application is ultrasonic-signature classification. SCDS is demonstrated by classifying ultrasonic signatures from thick-section, graphite/epoxy test panels.

SIGNATURE CLASSIFICATION DEVELOPMENT SYSTEM: SCDS is a software tool-kit designed to assist the research engineer in developing algorithms for classifying signatures. The system is fully programmable and graphical in nature, and allows the user to view interactively the processing and classification results on NDE signatures. The current version of SCDS assembles the tools needed to: select signatures for analysis, assign classification categories, perform digital signal processing (DSP), define gates or subsets of the signal, perform feature vector generation, and train artificial neural networks. Future versions of SCDS will include statistical classifiers, and a source-code generator to transition the classification algorithms into run-time applications.

The prototype, SCDS Version 1.02, runs on an IBM® PS/2® or AT-compatible computer operating under Microsoft® Windows™ 3.1 or above. SCDS Version 1.02 contains an Ultrasonic Library for the analysis of ultrasonic signatures, but will support analysis of any signature that is a function of a single variable (e.g. amplitude as a function of time). The main benefits of SCDS are the abilities to process NDE signatures interactively, and to develop ANN classifiers from a single, self-contained software product.

SCDS Version 1.02 has the following capabilities:

selection of data files and signatures,
assignment of classification categories,
random assignment of signatures to training, testing, and validation sets,
selection of DSP functions, templates, and gates,
selection and calculation of signature feature parameters,
batch mode processing of the data and feature generation,

classification of feature vectors via artificial neural networks,
graphical review of classification results.

SCDS User Interface: The SCDS user-interface is developed for Microsoft® Windows™. All displays in the SCDS graphical user-interface are developed using Microsoft® Visual Basic™, an event-driven high-level language for Microsoft® Windows™ that supports dynamic-link libraries [12]. An example window of the user-interface is shown in Figure 1. To increase the speed of processing, some process control and computations are performed in dynamic-link-library routines written in Borland® C++, Version 4.02.

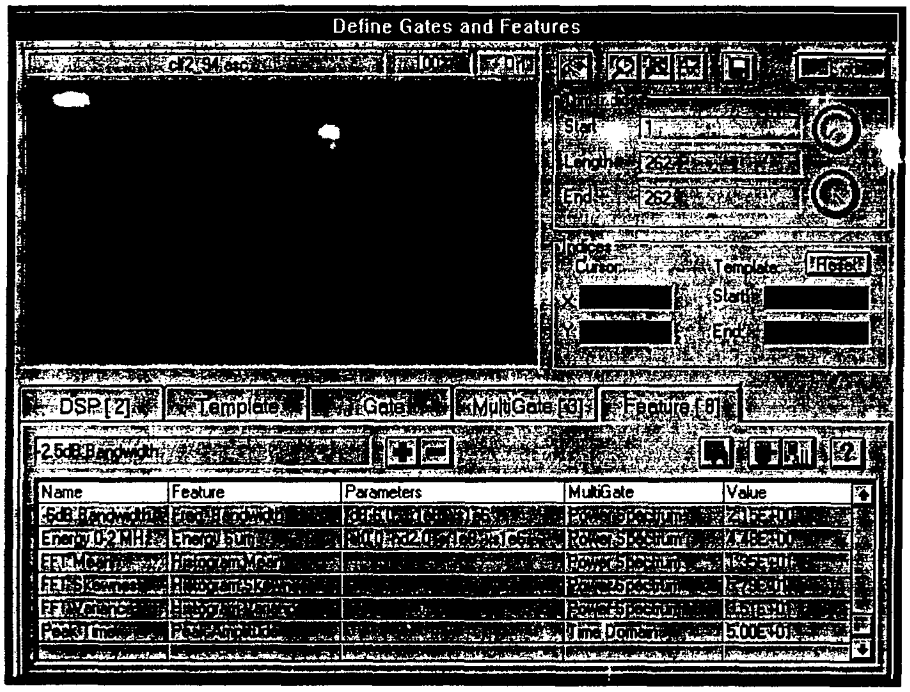

Figure 1. SCDS Define Gates and Features Window

SCDS Data-Processing Module: The SCDS data-processing module assists the user in processing the signatures and generating input feature-vectors for the ANN. The processing module supports digital signal processing, templates to locate discontinuities in the signatures, definition of gates and grouping of gates into multigates, and generation of features based on the gates and multigates. Processing routines are accessed via links to the SCDS functional libraries. On-line help provides a detailed description of each available SCDS library function and optional script-control parameters for the functions.

SCDS extracts features from gated, or sub-selected, portions of the NDE signature. A signature gate can be a fixed gate, with a specific starting and ending index, or can be a variable gate, where templates are used to locate the discontinuities in the signature and define the edges of the gate. Preand post-processing of the signature can extract the discontinuities and transform the signature prior to calculation of the feature parameters. Gates may be defined in different signal domains, for example, time domain, frequency domain, or discrete-wavelet domain. If desired, gates can be combined into multigates so that unwanted portions of the signal can be removed.

The SCDS *Define Gates and Features* window is shown in Figure 1, where an ultrasonic signature (contamination defect recorded from a graphic/epoxy test panel) is displayed. From the *Feature Tab*, the user can select feature routines from the SCDS Library and apply the feature routines to a particular user-defined gate or multigate. In Figure 1, five features are defined for the frequency domain (power spectrum), and one feature is defined for the time domain. By selecting the *Calculator Button* in the *Feature Tab,* SCDS will interactively perform the signal processing and gating, and display the calculated features in a table format.

The SCDS interactive environment temporarily records all signal definitions (data files, class assignments) and data processing routines (DSP, templates, gates, features) in a Microsoft® Access™ database. For permanent storage, this information is recorded in a project file. SCDS uses the project file while executing in a batch, non-interactive, mode to generate feature output files.

SCDS Signature Classification: SCDS Version 1.02 provides a user-friendly, graphical interface for a three-layer, feed-forward, back-propagation neural network. Other architectures and learning algorithms will be added in later versions of SCDS. In addition, SCDS links to the NeuralWorks Professional II/Plus, Version 4.2 for additional ANN learning algorithms [13].

SCDS Source Code Generation: A planned capability of SCDS is to provide the source code that implements the developed classification algorithm. The C source-code will include: 1) signal processing, templates, and gates, 2) generation of parameter features, and 3) the classification algorithm. All processing will be built into a single function call, requiring only the signature as the input and returning the classification of the signature as the output. The C source-code may then be integrated directly into automated NDE equipment in the field or laboratory.

APPLICATION TO COMPOSITE STRUCTURES: The U.S. Navy is increasing the use of fiber-reinforced composites in structures because of the potential for weight, cost, and signature reduction, as well as increased corrosion resistance [14]. Current and future applications of composites include: deckhouses, propulsion shafts, machinery foundations, air flasks, masts, and heat exchangers.

Unlike metallic structures, the effect of defects on the structural integrity of an advanced, composite material is difficult to assess because the inhomogeneity and anisotropy of the composite material does not produce a predominant failure mode. Each defect type results in a degradation of a specific mechanical property. For example, voids affect a wide variety of mechanical properties, but have the greatest effect on the interlaminar shear strength [15]. Olster [16] demonstrated that the interlaminar shear strength would decrease approximately ten percent for each one percent increase in void content. Rhodes [17] showed that a paper inclusion, such as the backing paper from prepreg material, decreased the compressive strength of the graphite/epoxy composite by 25 percent. Gerharz and Schutz [18] investigated the effect of delaminations on composites, and observed that delaminations also reduced the compressive strength of the material, resulting in a buckling failure mode. Lastly, matrix cracking may cause a reduction in shear, compressive and flexural strength [18] as well as initiate delaminations [19].

Because each defect type results in a degradation of a specific mechanical property, classification of the defect type will provide additional information to determine whether the composite material is suitable for the intended structural application. Furthermore, the ability to classify the defect type may reduce production and maintenance cost by permitting defect specific acceptance criteria, thus reducing or eliminating the rejection of benign defect types.

CASE STUDY: Seven, 4" x 4" x 1" graphite epoxy test panels were fabricated from 192 plies of Fiberite HYE2048A1A graphite epoxy prepreg tape in a [0/90]s lay up. Six of the panels were made with programmed defects, as shown in Table I. Two panels were produced containing delaminations, two with porosity, and two with contamination. Each panel was constructed by co-curing two fault-free sub-panels around a middle sub-panel containing the defect. The sub-panels embedded with porosity defects were twenty plies thick and the other defect sub-panels were eight plies thick. The middle sub-panels were placed at one-eighth and one-half of the depth of the test panels. Before insertion into the full-thickness test panel, each sub-panel was inspected using an ultrasonic C-scan system to verify the location and presence of the defects. A reference standard was constructed in a similar manner except that no defects were introduced into the middle sub-panel.

Table I. Graphite/epoxy test block construction

Id	Description	Sub-panel Thickness	Sub-panel Placement	Plies
A2	Reference	8-Ply	1/2 Thickness	92-99
B1	Delamination	8-Ply	1/8 Thickness	24-31
B2	Delamination	8-Ply	1/2 Thickness	92-99
D1	Porosity	20-Ply	1/8 Thickness	24-43
D2	Porosity	20-Ply	1/2 Thickness	87-106
F1	Contamination	8-Ply	1/8 Thickness	24-31
F2	Contamination	8-Ply	1/2 Thickness	92-99

Following lay-up and cure of the full-thickness test panels, a Sonix ultrasonic immersion system was used with a 5 MHz, 0.5-inch-diameter unfocused, immersion transducer to acquire the pulse-echo defect signature data from the seven panels. Before collection of the A-scans, each panel was C-scanned to guide the positioning of the transducer. A one-inch-square area was selected on each test panel as the site where a 10 x 10 grid was used to record A-scans at every 0.1 inch increment. A time gate was used to select the portion of the ultrasonic response containing the defect signature.

A total of 700 A-scans, 100 from each of the seven composite panels, were collected using the Sonix inspection system. The defect signatures were examined visually for signal strength and validity. Twenty-three signatures collected from panel F1 and ten signatures from panel F2 did not appear to be representative of the defect class and were eliminated from the data set.

SCDS Feature Generation: Brown and DeNale [11] demonstrated that planar and volumetric type defects exhibit different spreads in the power spectrum of the ultrasonic signature. To quantitatively characterize the signature spectral-spread, seven power-spectrum features were selected from the SCDS Ultrasonic Feature Library for input to the ANNs. In addition, one feature from the time domain, the peak signal amplitude, was selected to measure the presence of a defect. The eight selected features are described as follows:

(1)	<u>Peak Signal Amplitude, mVolts</u>-	peak amplitude of the time-based, ultrasonic signature.
(2)	<u>Bandwidth @ -2.5 dB Down, MHz</u>-	difference in frequency at the minimum and maximum energy crossing at the -2.5 dB threshold (75% amplitude).
(3)	<u>Bandwidth @ -6 dB Down, MHz</u>-	difference in frequency at the minimum and maximum energy crossing at the -6.0 dB threshold (50% amplitude).
(4)	<u>Bandwidth @ -12 dB Down, MHz</u>-	difference in frequency at the minimum and maximum energy crossing at the -12.0 dB threshold (25% amplitude).
(5)	<u>Spectral Energy from 0 to 2 MHz</u>-	sum of normalized spectral energy from 0 Hz to 2.0 MHz.
(6)	<u>Power Spectrum Mean, MHz</u>-	mean frequency value of the normalized power spectrum.
(7)	<u>Power Spectrum Variance, MHz^2</u>-	frequency variance of the normalized power spectrum.
(8)	<u>Power Spectrum Skewness, MHz^3</u>-	frequency skewness of the normalized power spectrum.

Prior to calculating each power spectrum, a Hanning filter [20] was used to reduce leakage of the spectral energy. In addition, before calculating the features, the energy (amplitude) of the power spectrum was normalized to a peak value of one. SCDS writes the feature vectors to a text file in a format consistent with NeuralWorks Professional II/Plus. The signatures were randomly subdivided by defect class into a training and test set.

Classification Results: Several learning algorithms available in NeuralWorks Professional II/Plus were used in this study: the back-propagation, the radial basis function, and learning vector quantization (LVQ) ANNs.

The radial basis function network (RBFN) can provide better generalization capability than the standard back-propagation ANN when the training data is sparse [13]. In contrast to the back-propagation ANN, which has a sigmoid transfer function for the hidden layer nodes, the RBFN uses a radially symmetric transfer function.

An LVQ network uses a competitive-learning approach to classify the input vectors [13]. This algorithm includes a Kohonen hidden layer and an output layer. The Kohonen layer generally requires more nodes than the hidden layer in back-propagation networks.

Table II lists the ANN training information . Four training trials were performed for each network type. First, the network was trained on 25% of the signatures and tested on the remaining 75%. Second, the network was trained on 50% of the signatures and tested on the remaining 50%. In the third and fourth trials, the training and testing sets were reversed from the first and second trials.

Table II. Neural Network Training Information

Network Type	% Training	% Testing	Hidden Nodes	Training Iterations
Back	25	75	3	16,107
Propagation	50	50	3	28,772
	50	50	3	45,000
	75	25	3	30,000
Radial Basis	25	75	8	45,261
Function	50	50	8	50,748
	50	50	8	30,000
	75	25	8	92,000
Learning Vector	25	75	13	22,500
Quantization	50	50	52	15,030
	50	50	52	14,985
	75	25	40	22,500

All network architectures have three layers, an input layer, hidden layer, and output layer. The input layers have eight nodes, one node for each signature feature extracted by SCDS. Prior to training the network, the input features are linearly scaled between 0 and 1. The output layers have four nodes, one for each of the desired classifications: nominal, delamination, porosity, and contamination. The number of hidden nodes varies with the learning algorithm. Through trial and error, the number of hidden nodes was reduced until the network performance degraded. A hidden layer with fewer nodes is desirable for two main reasons: 1) training and classification speeds increase with fewer hidden nodes, and 2) over-training of the network is reduced, improving the classification accuracy on test and field data.

The networks were trained using the “Save Best” option in NeuralWorks Professional II/Plus. During training, NeuralWorks periodically measures the classification accuracy of the network on the test set, saving the network weights when the classification accuracy improves. Training stops when the network performance does not improve after a specified number of training iterations.

The performance of the networks on the training and test sets is summarized in Tables III and IV, respectively. The three different network types correctly classified the porosity defect case for both the training and test sets. This was true even when only 25% of the signatures were used for training. No cases of a nominal, delamination or contamination signature were misclassified as a porosity defect (individual cases are not shown in tables). Further research is required: 1) to determine which features the ANNs clearly recognized as characteristic of the porosity defect population, and 2) to determine if the physical significance of these features is consistent with the differences in spectral spread observed in ultrasonic signatures from planar and volumetric weld defects [11].

Table III. Summary of Neural Network Performance on Training Set

Network Type	% Training	% Testing	% Correct Classified Training Set Nominal	Delamination	Porosity	Contamination
Back Propagation	25	75	100.0%	100.0%	100.0%	**85.7%**
	50	50	100.0%	100.0%	100.0%	**85.7%**
	50	50	**98.0%**	100.0%	100.0%	**92.8%**
	75	25	100.0%	100.0%	100.0%	**81.6%**
Radial Basis Function	25	75	**92.0%**	100.0%	100.0%	**81.0%**
	50	50	100.0%	100.0%	100.0%	**77.4%**
	50	50	100.0%	100.0%	100.0%	**69.9%**
	75	25	100.0%	**98.0%**	100.0%	**75.2%**
Learning Vector Quantization	25	75	100.0%	100.0%	100.0%	100.0%
	50	50	100.0%	100.0%	100.0%	**97.6%**
	50	50	100.0%	100.0%	100.0%	**97.6%**
	75	25	100.0%	100.0%	100.0%	**96.0%**

Table IV. Summary of Neural Network Performance on Test Set

Network Type	% Training	% Testing	% Correct Classified Test Set Nominal	Delamination	Porosity	Contamination
Back Propagation	25	75	**61.3%**	**90.7%**	100.0%	**92.0%**
	50	50	100.0%	100.0%	100.0%	**77.1%**
	50	50	**96.0%**	**97.0%**	100.0%	**83.3%**
	75	25	100.0%	100.0%	100.0%	**71.4%**
Radial Basis Function	25	75	**60.0%**	100.0%	100.0%	**80.0%**
	50	50	**98.0%**	100.0%	100.0%	**71.1%**
	50	50	100.0%	100.0%	100.0%	**77.4%**
	75	25	100.0%	100.0%	100.0%	**78.6%**
Learning Vector Quantization	25	75	**89.3%**	100.0%	100.0%	**91.2%**
	50	50	100.0%	100.0%	100.0%	**94.0%**
	50	50	100.0%	100.0%	100.0%	**90.5%**
	75	25	100.0%	**94.0%**	100.0%	**92.9%**

The networks have good success, although not perfect, distinguishing the two planar defects, delamination and contamination. In a few cases, the nominal case was misclassified as a planar defect. The training trials on only 25% of the population perform worse than the other trials, incorrectly classifying many nominal signatures. The variability in this training set does sufficiently represent the variability in the entire population.

The LVQ network performed better than either the back-propagation or radial basis function networks, with a higher classification accuracy achieved for the smaller training sets. The three LVQ networks trained on at least 50% of the data performed comparably, with the best performance achieved on the first 50-50 trial. For this best case, 94% of the contamination signatures in the test set were correctly classified, 5% were misclassified as delaminations, and the remaining 1% were misclassified as nominal. All other signatures were correctly classified.

The two planar defects, delaminations and contaminations, result in reductions in the compressive strength of the composite. When these defects are considered equivalent, the network correctly classified over 99% of the planar defects.

The remaining 1% of the contamination signatures were misclassified as nominal, which may be indicative of the reference panel construction. Three defect-free sub-panels were co-cured to construct the reference panel. The interfaces of these sub-panels are not perfect, and may be representative of a minor planar defect.

CONCLUSION: SCDS provides a user-friendly environment to develop signature-classification algorithms. With SCDS, an engineer can start with raw data and perform digital signal processing and feature extraction to develop a sophisticated classification algorithm using a variety of neural-network technologies. SCDS performs, or facilitates, all of the data handling and management tasks. The interactive graphical interface allows rapid what-if analyses. SCDS successfully built a classifier that distinguishes ultrasonic signatures from several defect types in thick-section graphite/epoxy composite test panels. Future enhancements to SCDS include: expanded neural-network training and testing capability; user-defined signal processing, templates, and features; statistical classification routines; and automated source-code-generation of the developed classification routine.

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